AI Adoption in Entrepreneurial Firms: The Influence of Innovativeness, Proactiveness, and Risk-Taking

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Abstract

This study investigates how Entrepreneurial Orientation (EO), comprising of innovativeness, proactiveness, and risk-taking, influences the adoption of artificial intelligence (AI) within entrepreneurial firms. Using the Technology Acceptance Model (TAM) as a theoretical framework, data were collected from 324 entrepreneurs through an online survey, designed to capture their perspectives on AI adoption without priming participants toward specific AI technologies. The findings reveal that firms exhibiting higher levels of EO are significantly more likely to adopt AI. This research expands the application of EO and TAM in the context of AI adoption, providing critical insights for understanding how entrepreneurial firms approach emerging technologies. By laying a foundation for future research, this study encourages the exploration of AI adoption through qualitative and mixed-method approaches, offering a pathway for a deeper understanding of the strategic role AI plays in small businesses.

Keywords: Innovation Adoption, Artificial Intelligence, Entrepreneurship, Business Strategy, Entrepreneurial Ecosystems.

1. Introduction

Entrepreneurs who have adopted AI into their processes are not seen in the literature (Obschonka & Audretsch, 2020; Schiavone et al., 2022; Giuggioli & Pellegrini, 2023; Truong et al., 2023). While large corporations have been at the forefront of AI integration, small businesses are increasingly recognizing the potential of AI to drive innovation and efficiency. Companies like Amazon, Microsoft, Google, Meta and OpenAI have created enterprise AI tools that make machine learning, deep learning, computer vision, natural language processing, generative AI and other forms of AI more accessible. Now that various forms of AI are more accessible, the perspectives of smaller, agile firms on AI adoption can now contribute to academic literature.

In this study, we aim to capture the perspectives of entrepreneurs across a broad spectrum that includes those who occasionally sell products online to those running established companies. To achieve this, we utilized Prolific's online survey platform and relied on their vetting process to only include participants who identify as currently engaged in entrepreneurship.

By including a diverse range of entrepreneurs, we can uncover unique perspectives associated with AI adoption that might otherwise be overlooked. We acknowledge the limitations related to self-identification and the varied background of the selected entrepreneurs. However, we believe that their contributions enrich our understanding of AI adoption in broader entrepreneurial contexts.

To better understand the types of entrepreneurs in our dataset, we employed entrepreneurial orientation. We posit that business owners can represent their firm's entrepreneurial orientation, as their businesses likely reflect their personal approaches. Since some businesses may not have enough employees for statistically significant internal studies, we generalized entrepreneurial orientation across multiple businesses available on the Prolific platform.

By hearing from entrepreneurs at all levels and not just those who meet stringent screening criteria, we provide insights that can inform entrepreneurial ecosystems and startup incubators. However, to better understand what characteristics make up the entrepreneurs selected for the study, we employed entrepreneurial orientation.

High levels of entrepreneurial orientation (EO), which includes innovativeness, proactiveness, and risk-taking, has been shown to influence a firm's likelihood of adopting new technologies. Firms often view new technologies as resources to gain a competitive edge. As technology becomes more accessible, businesses can leverage these advancements for competitiveness. However, the

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relationship between EO and AI adoption has not been thoroughly investigated, primarily because the current state of AI is recent and was previously impossible to study. This study seeks to address this gap by examining how the dimensions of EO impact AI adoption in entrepreneurial firms, using the Technology Acceptance Model (TAM) as the theoretical framework.

Previous research on the relationship between EO and TAM did not include technologies that mimic human cognition at the level of AI in 2024. While big data and cloud computing have been studied using EO and TAM, they do not present the same risks and opportunities as AI technologies. Typical risks associated with big data and cloud computing involve cybersecurity concerns, such as protecting data in the cloud from external threats. While important, these risks are geared toward preventing nefarious actions by outside entities and not from the technology itself.

Unlike big data and cloud computing, which pose external risks like cybersecurity threats, AI presents more intrinsic risks. Agentic AI systems can make biased decisions with greater consequences for businesses and society. The black-box nature of AI means the decision-making processes are not fully understood (Castelvecchi, 2016). This distinction further underscores the novelty of our study by considering EO and TAM in relation to the advanced capabilities AI in 2024.

Although AI is not a new topic and aspects of AI existed before 2022, the current capabilities and access to popular forms of AI have only recently become available to all entrepreneurs. In addition, entrepreneurs needed time to form an opinion about AI and witness the risks and opportunities of AI adoption in their industry. Even if there are current studies on the topic, research in this area is still new, and similar studies may yield different results. Having different results in similar studies creates more conversation to further address the issue of understanding the adoption of AI for entrepreneurs empirically.

Utilizing a survey of 324 entrepreneurs from diverse business industries and sizes, this study employed the technology acceptance model (TAM) to measure AI adoption levels. This study intentionally left the type of AI unspecified in the survey, allowing participants to respond based on their general understanding of AI. By avoiding specific references to technologies like ChatGPT, the survey was designed to capture a broader view of how entrepreneurs perceive and adopt AI without introducing bias.

The findings revealed that entrepreneurial orientation predicts AI adoption, explaining 37.8% of the variance in AI adoption. This level of variance indicates that the characteristics associated with EO are strong predictors of whether a firm will adopt AI technologies. This is significant for entrepreneurial ecosystems to consider when deciding which firm are more likely to benefit from receiving AI training and resources, as firms with a high degree of EO are more likely to perceive AI as necessary to drive success.

By understanding how EO traits predict AI adoption, entrepreneurial ecosystems and policymakers can tailor their support to foster AI integration, particularly in firms that demonstrate high levels of EO. To further contextualize AI adoption within entrepreneurial firms, the next section explores the broader literature on computer intelligence and its relevance to business contexts.

2. Literature Review

2.1 Computer Intelligence (AI vs BI)

Our study defines computer intelligence as the computer's ability to perform tasks typically assigned to humans or non-intelligent machines, following human instructions. AI, by contrast, refers to the computer’s ability to interpret external data, learn from it, and perform cognitive functions akin to human intelligence (Chalmers et al., 2020; Obschonka & Audretsch, 2020; Weber et al., 2022; Truong et al., 2023).

The term AI was first introduced at the Dartmouth Conference in 1955 (Ge et al., 2022) and is a departure from current business intelligence systems (BI) that can perform similar functions as AI (Negash, 2004; Watson & Wixom, 2007; Chalmers et al., 2020; Agerfalk, 2020). While BI systems are capable of predictive analysis, AI systems can operate more autonomously, interpreting data through machine learning and deep learning models (Manning et al., 2022).

Unlike BI systems, AI systems can act as an independent agent once trained, interpreting complex situations and making decisions without human guidance. AI systems, particularly those utilizing neural networks, function as black boxes, where decision-making processes are opaque and often difficult to interpret (Castelvecchi, 2016). This black-box nature poses significant risks, including biased decision-making and the generation of inaccurate outputs. Entrepreneurs must carefully consider the challenges when adopting AI technologies (Agerfalk, 2020; Rahaman, 2023).

For entrepreneurs, AI offers tools for predictions, image recognition, content creation, but also introduces challenges related to trust and reliability. Given these risks and opportunities, the adoption of AI

in entrepreneurial contexts requires a deep understanding of both its capabilities and its potential drawbacks. As we explore the relationship between entrepreneurial orientation and AI adoption, it is critical to consider how these factors shape decision-making in the adoption process. However, this study does not focus on risks associated with AI and only underscores the importance of risk awareness.

In the following sections, we review key theories of entrepreneurship and innovation to understand the decision-making processes involved in AI adoption.

2.2. Entrepreneurship

Entrepreneurship, in this study, is defined as the process of identifying, evaluating, and exploiting market opportunities through decisions that transform ideas into profitable ventures (Schumpeter, 1934; Shane & Venkataraman, 2000; Ahmad et al., 2019). This definition encompasses a broad range of entrepreneurs, from small-scale ventures to established firms. To support a comprehensive understanding of AI adoption, it is crucial to capture the perspectives of entrepreneurs across different levels of experience and resource availability, as smaller firms may encounter unique challenges compared to larger, well-resourced businesses.

By including entrepreneurs of varying sizes and capabilities, this study addresses the gap in the literature where smaller or emerging businesses are often overlooked in AI adoption research. Understanding how diverse entrepreneurs interact with AI technologies provides a more robust empirical foundation for future studies and practical insights into how AI can drive innovation at all levels of business. With this inclusive approach in mind, we now turn to effectuation theory to explore how entrepreneurs leverage available resources in decision-making.

2.3. Effectuation Theory

Effectuation theory explains how entrepreneurs make decisions by leveraging the resources they have at hand, focusing on flexibility and adaptability in uncertain environments rather than pursuing fixed long-term goals (Sarasvathy, 2009). Entrepreneurs following this approach prioritize controlling what they can, using their existing skills, networks, and opportunities to create value and navigate changing circumstances (Fisher, 2021).

With the increasing accessibility of advanced AI tools, effectuation-oriented entrepreneurs now have more resources available to them than ever before. Technologies like machine learning, natural language processing, and generative AI have become more affordable and user-friendly, enabling entrepreneurs to integrate AI into their processes without needing extensive technical expertise. This marks a significant shift from previous years when AI adoption was largely limited to larger, resource-rich firms (Obschonka & Audretsch, 2020).

As AI is now an easily accessible resource, entrepreneurs who embrace effectuation are more likely to adopt it, viewing AI as a tool that can enhance their existing capabilities. Building on effectuation, the resource-based view (RBV) further explores how entrepreneurs assess and leverage the internal resources of a firm, such as AI, to gain a competitive advantage.

2.4. Resource-Based View

The resource-based view (RBV) defines a firm's resources as anything that can be considered a strength or weakness, including tangible and intangible assets such as brand names, proprietary technologies, trade contracts, or efficient processes (Wernerfelt, 1984). RBV differentiates between a firm that focuses externally on customer needs and market demand, known as a product-based view, and one that emphasizes internal resources to create a competitive advantage, known as a resource-based view.

From the RBV perspective, firms that prioritize internal resources are better positioned to leverage innovations like AI. Rather than responding solely to market demands, these firms assess their unique assets, such as in-house knowledge, capital, or technological capabilities, to determine how AI can enhance their operations. By adopting AI, firms can improve internal efficiencies, build new competencies, and differentiate themselves in competitive markets.

With this in mind, we now turn to entrepreneurial orientation (EO) to further understand the different types of entrepreneurial firms.

2.5. Entrepreneurial Orientation

Entrepreneurial orientation (EO) refers to a firm's or individual's strategic mindset, characterized by three key dimensions: risk-taking, innovativeness, and proactiveness (Miller, 2011). Originally developed by Miller in his dissertation "Strategy Making in Context: Ten Empirical Archetypes" (1976), these dimensions describe how firms create strategies that allow them to explore opportunities outside the traditional market space. The concept was influenced by the work of Khandwalla (1977), Mintzberg (1973), Collin and Moore (1970), Normann (1971), Shapero (1975), and others.

Firms with high EO are more likely to pursue growth through innovation, taking calculated risks to develop new products or processes that differentiate them from competitors (Moreno & Casillas, 2008). These firms adopt a proactive approach, seeking out technological advancements like AI to improve internal efficiencies or create new market opportunities. While this pursuit of innovation carries inherent risks, it is often key to gaining a competitive advantage.

For this study, an entrepreneurial firm is defined as one that exhibits a high degree of EO. Such firms are generally more open to adopting technologies like AI as part of their strategy to achieve differentiation and success. To further understand how AI diffuses through entrepreneurial firms, we now turn to the diffusion of innovation framework.

2.6. Diffusion of Innovation

As artificial intelligence becomes more accessible, entrepreneurs find themselves at the beginning of the early adoption phase in the diffusion of innovation model. Popularized by Rogers (1962), diffusion of innovation theory outlines how technological innovations spread through communities over time. The early stages of diffusion are critical for entrepreneurs who seek to gain a competitive edge by adopting emerging technologies ahead of their competitors.

The first stage in this model, known as the innovator stage, refers to those entrepreneurs who had the resources and expertise to experiment with AI when its application was still largely confined to the computer science domain due to high costs and technical barriers (Agerfalk, 2020).

The early adoption phase, the second stage of the model, occurs when AI becomes more capable and user-friendly, requiring less technical expertise to implement. Entrepreneurs who adopt AI during this phase can capitalize on these advancements without the need for extensive technical knowledge, giving them a potential head start in their industries. As AI diffuses through the business ecosystem, those who wait too long to adopt may risk falling behind competitors who act more quickly.

Understanding the timing of AI adoption is crucial, as entrepreneurs who enter the early stages of diffusion stand to gain the most competitive advantage. With this foundation, we now turn to the Technology Acceptance Model (TAM) to further explore the factors influencing AI adoption.

2.7. Technology Acceptance Model

To understand the factors influencing AI adoption, we apply the Technology Acceptance Model (TAM), which focuses on three key factors: intention to use, perceived usefulness, and perceived ease of use (Davis, 1989). TAM helps explain how and why individuals adopt new technologies, and it is particularly relevant to entrepreneurs navigating AI integration.

In this study, TAM is applied as follows:

1. Intention to Use: Entrepreneurs must first develop an AI strategy to determine how much decision-making authority will be delegated to AI systems (Truong et al., 2023). This intent is crucial for understanding their readiness to adopt AI technologies.
2. Perceived Usefulness: This refers to the degree to which entrepreneurs believe that AI will improve their business performance. If AI is seen as enhancing productivity or innovation, its adoption becomes more likely (Davis, 1989).
3. Perceived Ease of Use: This measures the degree to which entrepreneurs believe that AI can be implemented with minimal effort. If AI is perceived as user-friendly and straightforward to integrate, it is more likely to be adopted (Davis, 1989).

By employing TAM, we can assess how these factors influence the decision-making process for AI adoption among entrepreneurs. Before diving deeper into the model, we will first explore the intersection between entrepreneurship and AI.

2.8. Entrepreneurship and Artificial Intelligence

The pace of AI development is unprecedented, with Obschonka & Audretsch (2020) noting that "entrepreneurship research seems not well-prepared and probably overwhelmed by the rapid changes and progress in the field of AI and big data." As AI evolves, it has the potential to significantly transform both entrepreneurship research and real-world practice, particularly in how entrepreneurs recognize opportunities, develop strategies, and interact with technologies (Obschonka & Audretsch, 2020).

Despite AI's growing influence, entrepreneurs who have integrated AI into their processes are largely absent from empirical research (Obschonka & Audretsch, 2020; Schiavone et al., 2022; Giuggioli & Pellegrini, 2023; Truong et al., 2023). While the literature acknowledges the transformative potential of AI on entrepreneurship (Blanco et al., 2023; Cockalo

et al., 2023), empirical studies focusing on how entrepreneurs actually adopt and implement AI remain scarce. This gap is particularly evident in industries such as travel and tourism, where studies like Filieri et al. (2021) have primarily explored conceptual frameworks for AI's positive impact, but lack concrete empirical evidence of AI adoption.

Scholars generally agree that AI can drive entrepreneurial activity and help identify new opportunities (Davidsson et al., 2018; Agrawal et al., 2017; Wang et al., 2022). However, while the promise of AI in entrepreneurship is well-documented, concerns about the ethical implications and governance around AI adoption persist. These concerns, though important, are beyond the scope of this study. Instead, our focus remains on understanding how entrepreneurs with a high degree of entrepreneurial orientation (EO), particularly those who are innovative, proactive, and willing to take risks, are adopting AI as a strategic resource.

This leads us to the development of our hypotheses, which explore the relationship between EO and AI adoption through the lenses of TAM.

2.9. Hypotheses

Hypothesis 1 (H1): Firms with high entrepreneurial orientation have a strong AI adoption. This hypothesis aims to establish a foundational relationship between EO and AI adoption. While previous studies have correlated EO with the Technology Acceptance Model (TAM) (e.g., Gupta et al., 2023), it is essential to test whether this relationship holds specifically for AI adoption. AI represents a unique technological context that may differ from other technologies previously studied. Furthermore, entrepreneurs have only recently had the opportunity to experience AI sufficiently to form relevant opinions about its current state. Therefore, it is crucial to empirically validate that firms with higher EO are more likely to perceive AI as both useful and easy to use, key components of TAM. This hypothesis is grounded in the theory that entrepreneurial firms are generally more innovative and open to adopting new technologies (Miller, 1983). Model 2, presented in Table 3.0 (available upon request), tests this hypothesis by including EO as a predictor while controlling for demographic and contextual variables.

Hypothesis 2 (H2): Firms with high levels of proactiveness have a strong positive perception of AI adoption. This hypothesis focuses on the proactiveness dimension of EO. Proactiveness reflects a firm's tendency to anticipate and act on future needs and opportunities (Miller, 1983). By examining the relationship between proactiveness and AI adoption, this hypothesis tests effectuation theory, which suggests that entrepreneurs are expected to identify opportunities and act early. Proactive firms are likely to perceive AI as a useful strategic tool for gaining a competitive advantage, consistent with TAM's perceived usefulness component. This hypothesis also relates to the resource-based view, suggesting that proactive firms leverage AI to enhance their strategic position. Model 4, as shown in Table 3.0 (available upon request), tests this hypothesis by including the proactiveness dimension of EO as a predictor.

Hypothesis 3 (H3): Firms with high levels of risk-taking have a strong positive use of AI. This hypothesis examines the risk-taking dimension of EO. Risk-taking involves a firm's willingness to engage in ventures with uncertain outcomes (Miller, 1983). AI adoption can be perceived as a risky investment, whether in developing AI tools or using them for internal processes. This hypothesis posits that firms with a higher propensity for risk-taking are more likely to use AI extensively. Given the potential benefits and inherent risks of AI adoption, it is expected that high-risk firms will have a high level of AI use. Firms with higher risk tolerance are more likely to adopt AI despite the challenges, aligning with TAM's perceived ease of use, where firms that are comfortable with uncertainty are more likely to overcome barriers to adoption. Models 6 and 7, detailed in Table 3.0 (available upon request), test this hypothesis. Model 6 includes the control variables with actual use as the dependent variable, while Model 7 includes both the control variables and the risk-taking dimension of EO as the independent variable, with actual use as the dependent variable.

3. Methods

This study employs a survey to investigate the relationship between a firm's entrepreneurial orientation and its perspective on AI adoption. Participants were recruited via Prolific, an online platform commonly used for academic and market research, known for providing a diverse and vetted participant pool. Prolific's filtering system was used to specifically select respondents who self-identified as actively engaged in entrepreneurship, ensuring that the sample aligned with the study's focus on entrepreneurial firms.

Before beginning the survey, participants were provided with detailed information about the study's purpose, assured of the confidentiality of their responses, and given the option to withdraw at any point. The survey, administered via the Qualtrics platform, took approximately 10 minutes to complete. Participants were asked to provide demographic data

about themselves and their businesses, including the size of their firm, industry, and entrepreneurial experience.

Measures for all constructs were captured using a 7-point Likert scale, which is commonly employed in behavioral research to capture nuanced variations in attitudes and perceptions. This scale allowed for a more granular understanding of participants' perspectives on AI adoption, strategic orientation, and related constructs.

For the analysis, multiple regression was chosen as the primary method to test the hypotheses. While structural equation modeling (SEM) could offer additional insights by simultaneously assessing latent variables and paths, multiple regression provided a more straightforward approach to address the study's research question within the available scope. Future studies could extend this research by employing more complex analytical techniques like SEM to enrich the understanding of the relationships between entrepreneurial orientation (EO) and AI adoption.

3.1. Participants

A total of 324 participants were recruited using Prolific, an online platform that facilitates access to diverse samples. Participants were self-identified as entrepreneurs from various countries, ensuring a broad perspective on AI adoption.

3.2. Scale Development

The entrepreneurial orientation (EO) scale measured the combined dimensions of risk-taking, innovativeness, and proactiveness, following Miller (1989). All three dimensions were assessed using a 7-point Likert scale, allowing for a comprehensive measurement of EO in the entrepreneurial context. Example items include: **INN1 (Innovativeness)**: "In general, the top decision makers of my business favor: (1 = strong emphasis on the marketing of tried-and-true products or services, 7 = strong emphasis on R&D, technological leadership, and innovations)." **RIS1 (Risk-Taking)**: "In general, top managers of my business have: (1 = a strong proclivity for low-risk projects with normal and certain rates of return, 7 = a strong proclivity for high-risk projects with chances of very high returns)." **PRO1 (Proactiveness)**: "In dealing with your competitors, my business: (1 = typically responds to actions which competitors initiate, 7 = typically initiates actions which competitors then respond to)."

Although innovativeness was included as part of the combined EO scale, this study chose not to test it as a separate hypothesis. Prior research strongly supports the idea that high levels of innovativeness are generally associated with positive views on technology adoption. Therefore, testing proactiveness and risk-taking as individual predictors of AI adoption was deemed more likely to yield novel insights.

To assess AI adoption, the study employed the Technology Acceptance Model (TAM) scale. The TAM scale measured participants' perceptions of usefulness and ease of use of AI technologies, as well as their attitudes towards AI, behavioral intentions to use AI, and actual use of AI. Importantly, AI was presented in general terms, and specific questions about AI technologies were avoided. The purpose of the survey was to capture broad views on AI adoption without priming participants toward certain technologies, given the diversity of AI applications and entrepreneurial contexts across various countries and industries. Future studies may focus on specific AI technologies, but the aim of this study was to understand general perceptions.

Examples include:

- **Perceived Usefulness (PU1)**: "Using AI in my business would enable us to accomplish tasks more quickly."
- **Perceived Ease of Use (PE1)**: "Learning to operate AI would be easy for me."
- **Attitude Towards AI (ATT1)**: "In general, I have a positive opinion about Artificial Intelligence (AI)."
- **Behavioral Intention to Use AI (BI1)**: "If I have the facilities required for using AI, I intend to use it."
- **Actual Use of AI (AU3)**: "I trust that AI systems will not disclose my personal information."

3.3. Internal Consistency and Validity

Cronbach's alpha was used to assess the internal consistency of the EO and TAM scales. Cronbach's alpha values above 0.70 are generally considered acceptable, indicating good internal consistency (Nunnally, 1978). However, values between 0.60 and 0.70 can be acceptable in exploratory research (Hair et al, 2010). For this study, Cronbach alpha values above 0.60 are considered acceptable. The entire instrument, including the EO and TAM scales, showed a good internal consistency reliability at $\alpha = .956$ for 31 items.

In this study, it's important to note that Miller (1989) suggested that the EO dimensions should be considered together when assessing the internal reliability. The EO scale used for Firm Strategy Type showed good internal consistency reliability at $\alpha = .865$ for 9 items. The sub-dimensions of EO had the following internal consistency reliability,

innovativeness is at α = .669 for 3 items, proactiveness is at α = .694 for 3 items, and risk taking is at α = .779 for 3 items. The model fit statistics for EO is (x^2 = 30.629, df = 25: CFI = .994, TLI.992, RMSEA = 0.026). These fit indices suggest that the measurement model for EO is appropriate and that the observed variables adequately represent the underlying constructs.

The TAM scale used for AI adoption showed excellent internal consistency reliability at α =.964 for 22 items. The sub-dimensions of TAM had the following internal consistency reliability, perceived usefulness is at α = .967 for 6 items, perceived ease of use is at α = .940 for 6 items, attitude towards use is at α = .950 for 3 items, behavioral intent to use is at α =.930 for 3 items, actual use is at α = .939 for 4 items. The model fit statistics for AI Adoption are χ^2 = 375.415, df = 187; CFI = 0.977, TLI = 0.972, RMSEA = 0.056. These fit indices suggest that the measurement model for the TAM constructs is appropriate and that the observed variables adequately represent the underlying constructs.

The correlation matrix was analyzed, revealing low to moderate correlations between the constructs of entrepreneurial orientation (INN, PRO, RIS) and the dependent variables (PU, PE, ATT BI, AU). These low to moderate correlations suggest that while the constructs are related, they remain distinct, supporting discriminant validity.

3.4. Control Variables

The control variables included country of residence, age, years of business operation, gender, and education. These variables were selected based on theoretical and empirical evidence suggesting their potential influence on technology adoption.

These control variables were included to account for potential confounding effects and to isolate the impact of entrepreneurial orientation (EO) on AI adoption. However, it is acknowledged that some control variables, such as age or education, could potentially act as additional predictors of AI adoption. Their inclusion allows for a more nuanced understanding of how demographic and contextual factors interact with the main predictors.

The results of the multiple regression analysis revealed that EO significantly predicts AI adoption, even after controlling for these demographic and contextual factors. However, the relationship between certain control variables and the predictors, such as age or education, could be explored further in future studies to determine whether they act as moderators or additional predictors in AI adoption.

4. Results

4.1. Descriptive Statistics

Table 1 presents the demographic characteristics of the entrepreneurs. The sample consists of 324 respondents, with a balanced gender distribution: 50.6% female (n=164), 47.5% male (n=154), 1.5% non-binary (n=5), and 0.3% trans-male (n=1).

Most entrepreneurs fall within the age range of 31-40 years (32.1%, n=104), followed by 21-30 years (28.4%, n=92), 41-50 years (18.5%, n=60), and more than 51 years (19.8%, n=64). A small proportion of participants are aged 18-20 years (1.2%, n=4).

Entrepreneurs are predominantly from the United Kingdom (28.1%, n=91) and the United States (27.5%, n=89). Other notable countries of residence include South Africa (19.8%, n=64) and Canada (6.8%, n=22). The remaining participants (17.8%, n=58) are from various other countries.

The highest level of education attained by entrepreneurs varies, with the largest group holding a bachelor's degree (45.4%, n=147). Other educational levels include high school (17.3%, n=56), only certification (15.1%, n=49), master's degree (21.9%, n=65), and doctorate (2.2%, n=7).

The duration for which entrepreneurs' businesses have been operating is diverse. The largest group has been in operation for 1-3 years (35.5%, n=115), followed by those operating for more than 10 years (22.2%, n=72), 4-6 years (21.9%, n=71), 7-10 years (10.5%, n=34), and less than 1 year (9.9%, n=32).

A significant portion of participants are not members of an entrepreneurial ecosystem (70.1%, n=227), while 29.9% (n=97) are members.

These demographic insights provide a comprehensive overview of the entrepreneurs participating in the study, highlighting the diversity in gender, age, country of residence, educational attainment, business operating years, and entrepreneurial ecosystem membership. This diversity enriches the study by ensuring a wide range of perspectives on AI adoption, thereby enhancing the generalizability of the findings.

The descriptive statistics for both EO and AI Adoption provide a comprehensive overview of the firms' strategic orientation and their perceptions and behaviors regarding AI adoption. The average score for entrepreneurial orientation is 3.5494, indicating moderate levels of entrepreneurial orientation among the firms. Similarly, the overall mean score for AI Adoption is 4.9144, which, while indicating a generally positive AI adoption, it still falls within the moderate to high-moderate range on a 7-point Likert

scale. This suggests that there is recognition of the value and ease of adopting AI technologies.

4.2. Multiple Regression

Multiple regression analysis was conducted to test the hypotheses and examine the relationships between EO and AI adoption, controlling for several demographic and contextual variables. The study controlled for gender, country of residence, age groups, years of business operation, and education to understand if these factors had a statistical impact on the perception of AI adoption. The results from Table 3.0 available upon request.

The analysis revealed that the control variables explained 20% of the variance in AI adoption, $R^2 = 0.203$, $F(36, 287) = 2.033$, $p < .001$ (Model 1, Table 3.0). Among the control variables, the most significant predictors were country of residence in South Africa ($\beta = 0.296$, $t(287) = 4.266$, $p < .001$), country of residence in the United States ($\beta = 0.169$, $t(287) = 2.548$, $p = .011$), age group 41–50 years ($\beta = -0.150$, $t(287) = -2.348$, $p = .020$), and business operations with more than 10 years in service ($\beta = -0.150$, $t(287) = -2.167$, $p = .031$).

Table 2. Entrepreneurial Orientation and AI Adoption

Factor	Mean	SD
Entrepreneurial Orientation	**3.5494**	**1.18806**
Innovativeness	3.4331	1.38173
Proactiveness	3.5988	1.33881
Risk-Taking	3.6163	1.37869
AI Adoption	**4.9144**	**1.18351**
Perceived Use	5.1312	1.54199
Perceived Ease	5.1790	1.22110
Attitude Towards Use	5.0412	1.45723
Behavioral Intent	5.2222	1.51225
Actual Use	3.8665	1.51455

To test the hypothesis that firms with high EO have a strong positive perception of AI adoption (H1), the study included EO as a predictor in the regression model while controlling demographic and contextual variables. This model explained 37.8% of the variance in AI adoption, $R^2 = 0.378$, $F(37, 286) = 4.705$, $p < .001$ (Model 2, Table 3.0). EO was found to be a significant positive predictor of AI adoption ($\beta = 0.475$, $t(286) = 8.977$, $p < .001$). These results support the hypothesis that higher levels of EO are associated with higher AI adoption.

To test the hypothesis that proactive firms have a strong positive perception of AI adoption (H2), a multiple regression analysis was conducted with the control variables. The analysis revealed that the model, including the control variables and the predictor variable of proactiveness, explained 30% of the variance in AI adoption, $R^2 = 0.304$, $F(37, 286) = 3.371$, $p < .001$ (Model 4, Table 3.0). Proactiveness was found to be a significant positive predictor of AI adoption ($\beta = 0.358$, $t(286) = 6.424$, $p < .001$). These results support the hypothesis that firms with higher levels of proactiveness are more likely to have high AI adoption.

To test the hypothesis that firms with high levels of risk-taking have a strong positive use of AI (H3), two models were analyzed. Model 6 tested the control variables against the dependent variable actual use, while Model 7 included both the control variables and the predictor variable of risk-taking. The control variables as predictors of actual use explained 13% of the variance, $R^2 = 0.133$, $F(36, 287) = 1.223$, $p = .187$ (Model 6, Table 3.0). This indicates that the control variables are not statistically significant predictors of Actual Use.

When the risk-taking variable was added to the model, the variance explained increased to 20.5%, $R^2 = 0.205$, $F(37, 286) = 1.990$, $p < .001$ (Model 7, Table 3.0). Risk-taking was found to be a significant, though weak, positive predictor of actual use ($\beta = 0.299$, $t(286) = 5.079$, $p < .001$). Despite the overall model not being statistically significant due to the control variables, the inclusion of risk-taking as a predictor highlights its importance. Therefore, while the control variables are not significant predictors, risk-taking itself is a significant predictor of AI use, supporting H3.

5. Discussion

The moderate levels of entrepreneurial orientation (EO) and AI adoption observed in the dataset may be influenced by several factors. A significant portion of the firms (70.1%) are not members of an entrepreneurial ecosystem, which could impact their strategic orientation and openness to innovation. This lack of ecosystem participation may have contributed to lower scores on the 7-point scale. Future studies could explore how entrepreneurial ecosystems and other demographic variables influence AI adoption rates, providing deeper insights into how firms can enhance their AI adoption strategies.

The findings from the multiple regression analysis provide valuable insights into the relationship between EO and AI adoption while considering the impact of various demographic and contextual factors. The results support the hypotheses that higher levels of EO, particularly proactiveness and risk-taking, are associated with positive AI adoption. While the use of structural equation modeling (SEM) could further validate these relationships, multiple regression was employed here to provide initial empirical insights.

Future studies may extend these findings using SEM to explore more complex relationships between EO and AI adoption.

The control variables, including gender, country of residence, age groups, years of business operation, and education, explained 20% of the variance in AI adoption. Significant predictors included country of residence (South Africa and the United States), age group (41–50 years), and firms with more than 10 years in operation. These findings suggest that geographic and demographic factors play a role in shaping firms' perceptions of AI adoption. For instance, firms in certain regions may have more access to AI technologies and support systems, influencing their adoption rates. While these controls were not the focus of the study, they may serve as predictors in future research.

Including EO as a predictor in the regression model significantly increased the explained variance in AI adoption to 37.8%. This finding underscores the importance of EO in driving AI adoption. Firms with higher levels of EO are more likely to recognize the value and ease of adopting AI technologies. Although innovativeness was measured, it was not tested as a separate predictor, as prior research strongly supports its positive association with technology adoption. This study focused on proactiveness and risk-taking for a more nuanced examination of AI adoption behaviors.

Further analysis revealed that proactiveness is a significant predictor of AI adoption, explaining 30% of the variance. This supports Hypothesis 2 that proactive firms are more likely to adopt AI. Proactive firms are forward-looking and willing to embrace new opportunities, making them more inclined to adopt AI technologies to gain a competitive edge.

The analysis of risk-taking as a predictor of actual AI use revealed that while the control variables alone were not significant predictors, the inclusion of risk-taking increased the explained variance to 20.5%. This finding supports Hypothesis 3, which posits that firms with high levels of risk-taking are more likely to use AI technologies. Risk-taking firms are more willing to invest in and experiment with new technologies, despite the uncertainties involved. This willingness to take risks is crucial to a resource-based view, as AI represents a valuable resource that can enhance internal capabilities.

The moderate levels of EO and AI adoption observed in the dataset may be influenced by factors such as the firms' exclusion from entrepreneurial ecosystems and the demographic composition of the sample. Future research could explore these influences more thoroughly, while employing additional analytical techniques like SEM to enrich the findings.

6. Limitations

One of the primary limitations of this study is its cross-sectional design conducted across multiple firms rather than focusing on a single firm. While this approach enhances the generalizability of the findings, it also limits the depth of understanding that could be achieved by studying internal dynamics within a single firm. Future research could benefit from conducting longitudinal or within-firm studies.

Additionally, a mixed-methods or qualitative approach, such as case studies or interviews, could provide deeper insights into how smaller firms navigate AI adoption. These approaches could capture the nuances of AI adoption in smaller firms, complementing the findings from quantitative research and offering a more comprehensive understanding.

Another limitation lies in the reliance on Prolific's self-identified entrepreneurs as participants. While Prolific's vetting process was used to filter respondents, future studies could explore additional verification methods to ensure respondents fully represent the entrepreneurial population. Similarly, while this study utilized multiple regression to analyze the relationship between Entrepreneurial Orientation (EO) and AI adoption, more sophisticated analytical techniques like structural equation modeling (SEM) could further enrich the understanding of these relationships.

Lastly, this study focused on general perceptions of AI without delving into specific technologies, such as generative AI or machine learning. This broad framing was intentional to capture general attitudes toward AI adoption. However, future studies could explore specific AI technologies.

7. Conclusion

This study provides valuable insights into the relationship between Entrepreneurial Orientation (EO) and AI adoption within entrepreneurial firms, particularly regarding emerging AI technologies. By examining EO's core dimensions—innovativeness, proactiveness, and risk-taking—we have gained a detailed understanding of how these elements influence AI adoption. The findings indicate that firms with higher levels of EO are more likely to adopt AI, explaining a significant portion of the variance in AI adoption.

Additionally, this study expands the application of EO and the Technology Acceptance Model (TAM) to AI adoption, confirming that proactiveness and risk-taking are strong predictors. This demonstrates that EO is relevant not only to traditional technology

adoption but also extends to advanced technologies like AI.

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